Skills gaps, skill and labour shortages, and mismatch – Existing evidence

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Abstract

This document provides an overview of the scientific literature on skills gaps, skill and labour shortages, and mismatch. Given that the existing literature is vast, and that there exist a number of recent overviews of the literature, the aim is to explore the literature most relevant for SkiLMeeT. The overview therefore focuses on some considerations regarding the relevant concepts and measurement; the drivers of skills gaps and shortages and mismatch considered in SkiLMeeT, i.e. mainly the technological and green transitions, but also other megatrends; and pathways to reduce skills gaps and shortages and mismatch considered in SkiLMeeT, i.e. education (educational choice, the dual education system, re- and upskilling) and worker mobility. The document also indicates relevant policy initiatives as well as the specific contributions made by SkiLMeeT.

1. Introduction

European labour markets are currently affected by several megatrends, including digitalization (automation and artificial intelligence), the green transition, demographic change and the disruption of global value chains. Digitalization and the green transition in particular lead to a change in the demand for skills, potentially creating skill shortages and skills gaps. The project SkiLMeeT (Skills for Labour Markets in the Digital and Green Transition) therefore focuses on these two megatrends. SkiLMeeT project has three main scientific objectives:

1) Create indicators of skills gaps and shortages.
2) Analyse the drivers of skills gaps and shortages.
3) Analyse pathways to reduce skills gaps and shortages.

In doing so, SkiLMeeT uses novel empirical methods and data to generate new evidence, but also aims at taking advantage of existing knowledge. Given the importance of skill shortages and skills gaps, it is natural that there already exists a large number of analyses and initiatives, both research and policy oriented, dealing with these issues. In the following, we therefore give an overview of past and ongoing research and projects, with a particular focus on European initiatives. In doing so, we focus on the research projects which are most relevant for SkiLMeeT.[1] In the final section of the overview, we also indicate some of the most relevant policy initiatives related to SkiLMeeT. Extensive and excellent overviews of the research on the green transition in the Social and Human Sciences funded at the European level via Horizon 2020 (H2020) between 2017 and 2021 are provided by European Commission (2024a). European Commission (2024b) offers a corresponding overview of the research on the digital transition.

This report is structured along the main components of the SkiLMeeT project. Section 2 contains a discussion of the concept of skills gaps, skill shortages and mismatch, as well as related measurement issues and initiatives. Chapter 3 discusses drivers of skills gaps and shortages focusing on those mainly considered in SkiLMeeT: technological progress, the green transition, and additional megatrends, i.e.

[1] Extensive overviews of the academic literature on skills gaps and shortages can be found in McGuiness et al. (2018), Somers et al. (2019), and Brunello and Wruuck (2021).

demographic change, the disruption of global value chains, the Covid pandemic, and migration. Chapter 4 proceeds accordingly with the pathways to reduce skills gaps and mismatch, i.e. education and worker mobility. Chapter 5 summarizes and concludes the report.

2. Skills gaps, skill and labour shortages, and mismatch

2.1. Conceptual considerations

The megatrends mentioned in the introduction (the digital and green transitions, demographic change, Covid-19, and the disruption of global value chains) are massive challenges for firms and workers alike. These developments induce shifts in skill demand and supply (Handel, 2003; Cedefop, 20024): the demand side changes as firms have to restructure in light of changing customer demands, production technologies and costs, as well as the regulatory environment, particularly with respect to the green transition. The supply side changes because of demographic trends, educational expansion, or updated training curricula.

These changes in demand and supply may lead to skills gaps and skill and labour shortages. Labour shortages are generally defined as a situation where there are less workers available in the labour market than needed, i.e. overall labour demand exceeds overall labour supply. Skill shortages can generally be defined as a situation where the supply of workers with a specific type of skills is lower than the demand for workers with this type of skills. Similarly, skills gaps (or skill mismatch) can be defined as a situation where there is no perfect alignment between the skills supplied and the skills demanded. At the macro level, this implies a gap between the aggregate skill supply and demand, e.g. at the regional level; at the micro level, this implies a gap between workers' skills and the skills required for a specific job or in a specific occupation (Brunello & Wruuck, 2021). Resolving these different types of mismatch requires different strategies: mismatch at the macro level could be resolved by more workers mobility; mismatch at the micro level by re- and upskilling of workers. Furthermore, the type of skill considered (e.g. digital skills, green skills) plays a crucial role. The following sections therefore explore the respective skills in detail.

Importantly, skills gaps are generally defined conditional on prevailing labour-market and working conditions, including wages. However, these factors can also play an important role for labour and skill shortages and gaps (Cedefop, 2024).

These considerations imply that the measurement of labour shortages, skill shortages and skills gaps is not straightforward. Furthermore, analysing the factors leading to these shortages and gaps is crucial for determining appropriate policy responses. Before turning to those factors in Section 3, we discuss measurement issues in the following section.

2.2. Measurement

Given the various definitions discussed in the preceding section, there are a number of different measures that have been used as indicators of skill and labour shortages and gaps. OECD (2017) lists the three approaches featured in Table 1, as well as employer surveys as an additional approach. Employer surveys are a direct measure of eliciting shortages and gaps from the point of view of employers. However, they are highly subjective, and perceived shortages and gaps may come from unfavourable wage and working conditions, rather than true skill shortages. SkiLMeeT therefore does not focus on employer surveys, but on the remaining three types of indicators.

Table 1. Types of shortage analysis

Type of shortage analysis	Potential measures
Vacancy analysis	Vacancy duration; ratio vacancies to job seekers/unemployed (Beveridge curve)
Employment pressure analysis	Employment growth; hours growth; unemployment rates
Wage pressure analysis	Wage growth

Source: Adopted from OECD (2017).

These three types of indicators have strengths and weaknesses. The analysis of vacancies focuses directly on labour demand by quantifying the extent of recruitment activities of firms. The duration of vacancies is often used as a proxy for the difficulty of firms in recruiting workers (e.g. ELA, 2021). A high vacancy duration is interpreted as a situation where it is the more difficult for firms to recruit workers, and hence the higher are skill shortages. Relating vacancies to the unemployment rate (or to the number of job seekers) yields the Beveridge curve that allows for additional insights (Elsby et la., 2015). Movements along the Beveridge curve can be interpreted as reflecting business cycle conditions, whereas shifts of the Beveridge curve can be interpreted as changes in the matching efficiency of the labour market. Finally, the analysis of vacancies using big data also makes it possible to go into detail regarding different aspects of labour demand. In particular, it is possible to identify specific skills from online job vacancies, an issue discussed in the following sections.

Employment pressure analysis takes into account realised labour demand (in contrast to the analysis of vacancies, where labour demand may not be realised). The underlying idea is that fast employment growth, typically within an occupation, may indicate that labour supply may not be able to keep up with rising demand, leading to skill shortages. Other adjustment mechanisms are an increase in hours per workers, higher labour mobility (more people switch to another job) or an improvement of worker quality by re- and upskilling, leading to higher productivity (OECD, 2017). In a similar spirit as using employment as an indicator of employment pressure, one can use occupation-specific unemployment rates. Here, skills gaps can be identified when occupation-specific unemployment rates are particularly low.

Finally, wage pressure analysis takes into account the consequences of realised labour demand, i.e. the wage pressure that can result from a scarcity of labour. Indeed, Grois and Sondermann (2024) find in a panel of European firms with higher shortages pay a wage growth premium to keep and attract workers, increasingly so when they face excess demand.

The described approaches can be used individually, or they can be combined to construct composite indicators of skills gaps and shortages. This is done for example internationally by the OECD (OECD, 2017), and nationally by e.g. the German Labour Agency (Statistik der Bundesagentur für Arbeit, 2020) or by the UK Migration Advisory Committee (MAC, 2020).

SkiLMeeT contributes to the measurement of skills gaps, skill and labour shortages, and mismatch along several dimensions. First, it provides indicators for green and digital skills and specialized versus diversified skill sets, using measures of labour demand (from Online Job Vacancy (OJV) data) and labour supply. Second, it computes indicators for past, current and forecasted skill shortages and mismatches, also mapping the similarities and distances between occupations. Third, it provides measures of matching efficiency using Beveridge Curve-types analyses.

3. Drivers of skills gaps and mismatch

3.1. Technology

The SkiLMeeT project considers several drivers of technology. These drivers include robots, where an extensive literature and a good understanding of the labour-market impact exists, and artificial intelligence, where the evidence is beginning to emerge. Given that artificial intelligence has only been adopted on a large scale in recent years, and given the rapid technological advancements in this field, the evidence on the effects of artificial intelligence is less encompassing and conclusive than the evidence for robots. SkiLMeeT also makes use of patents as a measure of the speed of technological progress and the disruptive potential of specific technologies. In the following, the report therefore discusses the literature on robots, artificial intelligence and patents.

3.1.1. Robots

Over recent decades, the labour market consequences of industrial robots have received considerable attention in economic research and among the public. Rapid technological advancements have reshaped labour markets worldwide. In high-income countries, robot adoption has increased GDP, labour productivity, and wages (Graetz and Michaels, 2018). However, it has also raised concerns about potential job losses and polarization (Acemoglu & Loebbing, 2022).

The international evidence on the employment effects of robot exposure is mixed. On the one hand, robot adoption may directly reduce employment when the displacement effect prevails (Acemoglu & Restrepo, 2019). For instance, robot adoption reduced total employment in the US (Acemoglu & Restrepo, 2020; Borjas & Freeman, 2019) but not in other high-income countries such as Germany or Japan (Adachi et al., 2022; Dauth et al., 2021). Moreover, the employment effects of robot adoption appear to differ between countries at different development levels (de Vries et al., 2020) and with different levels of labour costs (Bachmann et al., 2024a).

Labour-saving technologies such as industrial robots primarily influence routine-intensive jobs, making them susceptible to replacement. This dynamic creates winners and losers in the technological transformation, with workers in routine professions often finding themselves disadvantaged (Johnson and Acemoglu, 2023). Robot adoption resulted in a decreased share of employment among routine manual workers (de Vries et al., 2020), low-skilled workers (Graetz and Michaels, 2018), and older workers (Albinowski & Lewandowski, 2024).

On the other hand, robot adoption induces ripple effects through increased activity thanks to productivity-enhancing technology (Duan et al., 2023; Koch et al., 2021) and demand for other sectors' output resulting from higher value-added and incomes in the technology-adopting sector (Alguacil et al., 2022; Autor & Salomons, 2018; Graetz & Michaels, 2018). Empirically, these positive effects tend to dominate over displacement effects in Europe, enhancing employment (Gregory et al., 2021).

Another important aspect of automation is its effect on workers' wages. In theory, robots and other labour-saving technologies should directly decrease the real wages of workers with a comparative advantage in performing displaced tasks. However, the productivity-boosting impacts of robots may increase wages. There is evidence that robot adoption harms wages in the US, especially among lower-educated workers performing easily automatable jobs (Acemoglu & Restrepo, 2020; Borjas & Freeman, 2019). In contrast, the negative effect on wages in the German manufacturing sector was offset by increased wages among jobs in services, leaving aggregate wages unaffected (Dauth et al., 2021). Firm-level evidence indicates that robot adoption increases wages in Spain, but only among automating firms (Koch et al., 2021). However, robot adoption led to a decrease of the labour share in France (Acemoglu et al., 2020), and a decrease in wages of blue-collar workers in the Netherlands (Acemoglu et al., 2023) and Denmark (Humlum, 2023). Barth et al. (2020) find an increase in wage premia among highly educated and a decrease among low-educated workers in Norway, contributing to wage polarisation. Similarly, Acemoglu & Restrepo (2022) indicate robots as an important driver of decreasing wages of routine workers in the US, which led to an increase in wage inequality.

3.1.2. Artificial intelligence

Artificial Intelligence (AI) is a key emerging technology that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions (OECD 2022). Especially its ability to learn with varying levels of autonomy distinguishes AI systems from earlier digital technologies and appeals to firms (Abrardi et al. 2022). Indeed, a rising number of European firms are currently adopting AI technologies. By 2023, 8% of all firms in Europe had adopted AI technologies, though strong discrepancies exist (European Commission 2023a). In some countries, more than 15% of firms have adopted AI technologies (e.g., Denmark, Finland, Luxembourg), while other countries display comparably low adoption rates of less than 4% (e.g. Romania, Bulgaria, Poland). The broad diffusion of AI underscores its growing relevance in modern economies. The underlying heterogeneity, however, also highlights the uneven impact and potential challenges across different regions, which is crucial for understanding regional labour-market dynamics and implementation of suitable policy measures.

Similarly to the impact of robot technology, the impact of AI on labour markets can be assessed with a task-based framework (Acemoglu & Autor 2011). On the one hand, AI may displace workers by automating tasks that were previously performed by labour, implying a reduction in labour demand for jobs associated with such tasks. For example, AI has the potential to perform many job tasks in white-collar occupations with high cognitive requirements but fewer physical and social activities (Engberg et al. 2023), such as data analysis or natural language processing (Felten et al. 2021, 2023). On the other hand, AI may increase labour demand in jobs where it enhances productivity, e.g., through cost savings or by the creation of new tasks that are complementary to labour (Acemoglu et al. 2022). Unlike previous technologies (such as computers and robots), which have primarily displaced low-skill, routine tasks, AI could therefore potentially displace activities associated with high-skilled jobs (Webb 2020). Consequently, AI may affect jobs differently than previous technologies (Tolan et al. 2021), requiring a reevaluation of technology-induced job structures, skill requirements, and labour market outcomes.

While AI does not display any discernible aggregate labour market effects yet in its current infancy stage (Acemoglu et al. 2022), its impact on firms' labour and skill demand has contributed to heterogenous implications across occupations, regions, and industries. In particular, AI has already affected the task structure of certain jobs (Acemoglu et al. 2022) by raising the demand for AI skills, especially in IT and other cognitively demanding occupations (Alekseeva et al. 2021). These task shifts align with mostly positive findings on employment in Europe (Pryotkova et al. 2024), though positive employment responses are concentrated in the service sector (Gathmann & Grimm 2022), and in occupations (Albanesi et al. 2023) and establishments (Peede & Stops 2024) with a highly skilled workforce. Combined, the existing literature suggests a positive relationship between rising AI adoption and employment with no major displacement effects yet. Wage responses, in turn, tend to be more mixed. Rising AI exposure has so far displayed no significant impact on wages, neither at the occupational (Georgieff 2024) nor at the local level (Gathmann & Grimm 2022). Micro-level evidence, however, suggests positive wage implications for high-skilled workers (Fossen & Sorgner 2022, Gonschor & Storm, 2025).

In summary, the rapid adoption of AI technologies and concurrent changes in jobs' task structures reinforce the need for continuous upskilling and reskilling, thereby highlighting the importance of developing adaptive pathways to address labour shortages. As AI adoption continues to rise, ensuring a skilled workforce that can complement AI technologies becomes crucial. This dynamic is essential for mitigating skill mismatches and ensuring that the benefits of AI are widely distributed, aligning with SkiLMeeT's core focus on addressing skill shortages and enhancing labour market adaptability.

3.1.3. Patents

Patents are widely recognized as a main indicator of technological change, and can also be viewed as a driver of technological change. Patents provide a wealth of quantitative data that can be used to measure technological progress. Metrics such as forward citations, patent family size, and patent renewals are commonly used to assess the value and impact of patents. Forward citations, for example, indicate the influence of a patent on subsequent innovations, while patent renewals suggest the commercial viability and sustained value of the patented technology.

One challenge in dealing with the information contained in patents is that they are available in text format. This implies that this information has to be processed to make it usable in quantitative analyses. Kelly et al. (2021) present a novel approach to measuring technological innovation using textual analysis of patent documents. They develop new indicators of technological innovation by analyzing the textual content of patent documents. These indicators identify important patents based on their textual similarity to previous and subsequent patents, highlighting patents that are distinct from prior work but related to future innovations – breakthrough patents, which represent a discontinuous change in the innovation space. Based on these indicators, the authors construct indices which capture the evolution of technological waves over a long period, from 1840 to the present. Key technological advancements driving these waves include: Electricity and transportation in the 1880s; Chemicals and electricity in the 1920s and 1930s; and Computers and communication technologies post-1980s.

Autor et al. (forthcoming) harness the concept of breakthrough patents by Kelly et al. (2021) to study the effects of technological change for the emergence and impact of new job categories over an 80-year period. They constructed a novel database of new job titles spanning eight decades, using U.S. Census microdata and patent-based measures of occupations' exposure to labour-augmenting and labour-automating innovations. The majority of current employment is in new job specialties introduced since 1940. However, the locus of new work creation has shifted from middle-paid production and clerical occupations (1940–1980) to high-paid professional and, secondarily, low-paid service occupations (since 1980). New work emerges in response to technological innovations that complement the outputs of occupations and demand shocks that raise occupational demand. Innovations that automate tasks or reduce occupational demand slow the emergence of new work. The flow of augmentation (labour-augmenting) and automation (labour-automating) innovations is positively correlated across occupations. Augmentation innovations boost occupational labour demand, while automation innovations depress it. The findings suggest that while new job categories can counterbalance some of the employment-eroding effects of automation, the overall impact on labour demand varies significantly depending on the nature of the technological innovations and the sectors affected.

Kogan et al. (2023) rely on patent data and job descriptions to study the effect of technological change on labour market outcomes. They construct measures of workers' exposure to labour-saving (automation) and labour-augmenting technologies by analyzing the textual similarity between patent documents and occupation task descriptions from the O*NET database. These measures capture the extent to which new technologies either substitute for or complement the tasks performed by workers in specific occupations. Labour-saving technologies predict significant earnings declines and a higher likelihood of job loss for all workers, regardless of their characteristics. Labour-augmenting technologies primarily predict earnings losses for older or highly-paid workers, suggesting that these workers may face challenges in adapting to new skill requirements. Despite the negative effects on individual workers, the study finds positive effects of labour-augmenting technologies on occupation-level employment and wage bills, indicating that these technologies create new job opportunities and increase overall labour demand. The authors develop a model which suggests that the negative effects of labour-augmenting technologies on older or highly-paid workers arise from the depreciation of their existing human capital and the costs of acquiring new skills. The findings underscore the importance of continuous skill development and adaptability in the face of rapidly evolving technologies.

Deming and Noray (2020) zoom in on occupations in the fields of Science, Technology, Engineering, and Mathematics (STEM). They find that the rapid pace of technological change in STEM fields leads to faster skill obsolescence. This results in a decline in the earnings premium for STEM graduates over time. They develop a model where the returns to work experience are a race between on-the-job learning and skill obsolescence. In faster-changing careers, skill obsolescence lowers the return to experience, flattening the age-earnings profile. The earnings premium for college graduates majoring in technology-intensive subjects such as computer science, engineering, and business declines rapidly as they gain experience. STEM graduates initially command higher starting salaries due to their job-relevant skills. However, as new skills are introduced to the workplace, the value of their existing skills diminishes, leading to a decline in earnings growth. As STEM graduates gain experience, they tend to move out of faster-changing occupations. This sorting is driven by the declining returns to experience in these fields due to skill obsolescence. High-ability workers are more likely to start in STEM fields but are no more likely to remain in these fields by mid-career.

The authors' findings suggest that technological change benefits skilled workers initially but also lead to faster skill obsolescence, which affects long-term earnings dynamics. The results highlight the importance of continuous learning and adaptability for STEM professionals. There is a need for education and training programs to keep pace with the rapid changes in skill requirements. Policymakers and educators should focus on developing lifelong learning opportunities and updating curricula to include emerging skills.

SkiLMeeT takes the literature on robots, AI and patents as starting point and makes several contributions. First, it analyses digitalisation, globalisation and supply factors as drivers of skill-use at work. Second it provides an analysis of the drivers of skill needs and shortages in the labour market.

3.2. Greening of the labour market

The European Green Deal (EGD) of the European Commission represents an unprecedented effort to accelerate the transition towards a clean, sustainable and smart economy. For policymakers, the impact of the EGD on jobs is of primary importance, especially in regions that heavily rely on polluting sectors and fossil fuels. However, establishing a clear definition of what is a green job has always been a major obstacle to conduct rigorous research on the labour market responses to environmental policies and to the adoption of green technologies. This obstacle arises because there is no widely accepted definition of what is green.

There are three broad approaches to define "what is green": the "process definition" and the "output definition" (Bontadini and Vona, 2023). The *process definition* uses the effective pollution content of production and thus of the occupations involved in such production. The main issue with the process approach is that data limitations make it virtually impossible to obtain a measure of the pollution content of products for multiple environmental problems and across several countries, sectors and years (Sato, 2014). The *output definition* is based on the potential of a product or a service to generate harmful impacts on the environment. A strand of research uses the output definition to infer the share of green jobs in a sector from the share of green production in that sector (Becker and Shadbegian, 2009; Elliott and Lindely, 2017), with three important limitations. First, it imposes a proportionality assumption between green production and green employment. Second, it does not allow to identify the specific types of workers and tasks that complement green activities. Third, data on green production are only available for the manufacturing sector.[2]

An alternative approach, conceptually tied to the *output definition*, is to employ a more granular task-based approach (Autor et al., 2003; Autor, 2013), in which tasks rather than products are the building blocks. This approach allows to disambiguate the definition of what is "green" in the context of labour. Implementing the task-based approach to study green jobs and skills requires appropriate data, specifically containing detailed information on the task and skill content of occupations, where an occupation is defined as a vector of tasks and skills.

Data including information on tasks and skills are well established only for the United States (US), with the online Occupational Information Network (O*NET). O*NET contains information on both tasks, i.e. what workers are expected to do at the workplace, (the 'demand side') and skills, i.e. the abilities and competences that workers should possess to perform work tasks (the 'supply side'). O*NET has a special section devoted to identify green jobs and tasks: the 'Green Economy Program'. This program is mostly inspired by the *output definition* and was developed to provide a definition of what is green. The information contained in the 'Green Economy Program' can be used to identify green jobs based on a binary definition of whether an occupation is considered either green or non-green.

The 'Green Economy Program' of O*NET identifies three groups of green occupations: (i) existing occupations that are expected to be in high demand due to the greening of the economy (*Green Increased Demand*); (ii) occupations that are expected to undergo significant changes in task content due to the greening of the economy (*Green-Enhanced Skills*); and (iii) new occupations in the green economy (*New & Emerging Green*). Occupations belonging to any of these groups can be considered as "green" in a binary fashion. However, exploiting a binary definition can lead to an overestimation of the size of the green economy as some occupations considered green, such as construction workers, also engage in non-green production activities. Early papers use the binary definition to reveal some interesting facts on the skill requirement of green jobs (Consoli et al., 2016; Bowen et al., 2019). Consoli

[2] Several (if not most) green jobs are created outside manufacturing in construction, waste management and power generation.

et al. (2016) find that green jobs require more on-the-job training and non-routine cognitive skills than non-green jobs, but not more years of schooling.

To overcome such measurement problems, Vona et al. (2018) propose to exploit the very rich information on the task content of occupations in O*NET within the US labour market. In fact, for a subset of green occupation, O*NET reports total tasks and green tasks, allowing for a continuous measure, defined as the greenness of an occupation, that is the ratio between green tasks and total tasks. There are two possible interpretations of the greenness indicator. First, occupational greenness can be interpreted as the amount of time spent on green activities and technologies in the average job post within a certain occupation. Importantly, the indicator captures the fact that most occupations are neither green nor non-green, and often occupations are transitioning towards greener task configurations. Second, the greenness indicator is related to the underlined aggregation of job posts in an economy. Vona et al. (2018) show that, within occupations classified as green, only the most uncontroversial occupations like Environmental Engineers, Solar Photovoltaic Installers or Biomass Plant Technicians are fully green (Greenness score=1). Conversely, occupations that, on average, encompass both green and non-green tasks have an intermediate Greenness score, such as Electrical Engineers, Automotive Specialty Technicians or Roofers (Greenness score between 0.3 and 0.5). Finally, there is a group of occupations for which, on average, green tasks are marginal, such as traditional Engineering occupations, Marketing Managers or Construction Workers (Table 2). In a nutshell, such a continuous indicator allows to purge from an analysis of green jobs those occupations that may be classified as green when using a dichotomous approach, but that, according to the task approach, have only a low share of green-related activities or tasks.

Table 2. Examples of green occupations by level of "Greenness"

	***Greenness*=1**	***Greenness* btw 0.5 and 0.3**	***Greenness*<0.3**
Green Enhanced Occupations	Environmental Engineers, Environ Science Technicians, Hazardous Material Removers	Aerospace Engineers, Atmospheric and Space Scientists, Automotive Specialty Technicians, Roofers	Construction Workers, Maintenance & Repair Workers, Inspectors, Marketing Managers

New and Emerging Green Occupations	Wind Energy Engineers, Fuel Cell Technicians, Recycling Coordinators	Electrical Engineering Technologists, Biochemical Engineers, Supply Chain Managers, Precision Agriculture Technicians	Traditional Engineering Occupations, Transportation Planners, Compliance Managers

Source: adapted from Vona et al. (2018)

To further stress the advantage of a continuous measure of the *greenness* of an occupation compared to a binary classification, Vona et al. (2019) propose a task-based measure of green employment that reweighs occupational employment shares by their *greenness*. The authors show that the share of green employment, based on the continuous occupational Greenness indicator, closely matches the share of green employment obtained with the Green Good and Service Survey of the Bureau of Labour Statistics (BLS), which is approximately 2-3% of total employment. Remarkably, Bontadini and Vona (2023) and Cedefop (2019) find very similar shares of, respectively, green production and green jobs using different data sources. In turn, the share of green employment using the O*NET binary measure is approximately 20%, clearly over-estimating the size of the green economy.

A natural follow-up on the definition of green jobs is the estimation of local job multipliers, pioneered by Moretti (2010), due to a green expansion. Although the literature is limited to the US, it provides some important insights. Vona et al. (2019) show that the green job multiplier is between 2 and 4, thus in the upper range together with high-tech activities. Popp et al. (2021) qualify the Vona et al. (2019) estimate. Lastly, in an analysis for Spain, Fabra et al. (2023) find positive local multipliers resulting from the expansion of the clean energy sector, mainly the solar one. Despite being important, the analysis is limited to a subset of the energy sector. In a recent working paper, Frattini et al (2024) use green production data based on Bontadini and Vona (2023) to estimate green local job multipliers. They find that green local job multipliers are most pronounced in the construction- and knowledge-intensive service sectors.

Another important application of the task-based approach is in the context of the identification of the competences and skills relevant for specific jobs, including green ones. Skills are important to assess both the distributional and aggregated effects of environmental policies. Regarding distributional effects, Vona et al. (2018) propose to use the task-based approach to reveal comparative advantage schedules, searching for the skills or productive factors that are better suited to perform certain tasks.

In a nutshell, this implies correlating the score (1-5) of importance that a skill has within an occupation with the *greenness* of that occupation.[3] Using this procedure, Vona et al. (2018) obtain 16 green skills, which are ranked and clustered together using principal component analysis. The resulting four groups of green skills are: i) Engineering and Technical, ii) Operation Management, iii) Monitoring, and iv) Science.

Table 3. Green Skills

	Engineering & Technical
2C3b	Engineering and Technology
2C3c	Design
2C3d	Building and Construction
2C3e	Mechanical
4A3b2	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
4A1b3	Estimating the Quantifiable Characteristics of Products, Events, or Information
	Operation Management
2B4g	Systems Analysis
2B4h	Systems Evaluation
4A2b3	Updating and Using Relevant Knowledge
4A4b6	Provide Consultation and Advice to Others
	Monitoring
2C8b	Law and Government
4A2a3	Evaluating Information to Determine Compliance with Standards
	Science
2C4b	Physics
2C4d	Biology

Source: adapted from Vona et al, (2018)

The data-driven approach from Vona et al. (2018) to identify green skills can be used for several other purposes relevant for the impact of the green transition and of climate change in the labour market. For instance, a researcher can be interested in identifying "brown" skills by replacing brown with green tasks or the skill set of workers more exposed to climate shocks. Also, it is possible to partition the set of green tasks by the type of green technology using the rich text contained in the definition of specific tasks.

[3] O*NET contains for each occupation a set of relevant skills rated in terms of importance from 1 to 5.

Green skills have been found to be important to mediate the economic effect of green policies, such as subsidies to renewable, energy efficiency, brownfield redevelopment and low-carbon infrastructure. Popp et al. (2021) show that the net job creation of the green part of the US American Recovery and Reinvestment Act (ARRA) was much larger in US commuting zones with a larger fraction of workers with the appropriate green skills (measured as the share of workers in the upper quartile of the nation-wide green skill distribution), which also received a larger fraction of green spending and were growing relatively faster before the 2008 financial crisis.

A natural follow-up of the measurement of green skills is the estimation of reallocation costs and distributional effects. A strand of research in labour economics uses the task-based approach to answer the broader question of which are the consequences of job-to-job transitions and reallocations in terms of earnings, employability and other labour-market outcomes (Gathmann and Schönberg, 2010 – more on the topic in section 4.1.1). This research strand finds that workers' reallocation costs mostly depend on the skill similarity between origin and destination occupations. Researchers use various measures of skill similarity (i.e. the angular separator distance as in Gathmann and Schönberg, 2010) for two paired occupations or groups of occupations (brown vs. green). Despite not applying these methodologies directly, the literature draws insights into this theme. Vona et al. (2018) reveal that green and brown jobs, within the same SOC 2-digits sector, are quite similar in terms of green skills, excluding construction (green) and extraction (brown) workers. Further, Popp et al. (2021) show that the green stimulus package of Obama benefited mostly low-skilled manual workers in construction.

To conclude, data limitations prevent to conduct similar analyses in most European countries where O*NET is not available. However, using O*NET skills and tasks for EU occupations remains a promising second-best option to overcome data limitations. The practical implementation relies on the quality of available crosswalks between the US SOC classification and the EU ISCO classification. The report of Gilli et al. (2020) highlights some drawbacks of using this ISCO-SOC cross-walking because ISCO occupational data are aggregated at the 3-digit level. In general, Gilli et al. (2020) conclude that the quality of the crosswalk is not sufficient to use it to measure green employment in the EU. This conclusion also largely depends on the level of aggregation in EU employment data. In fact, EU Labour Force Survey data are available only at the 3-digit ISCO level, with a limited level of sectoral aggregation (1-digit NACE), or at 1-digit ISCO level and 2-digit NACE level, as for the data used in Marin and Vona (2019). Employment data for regional statistics are even more aggregated in the EU. Even if a researcher had a perfect EU-crafted measure of occupational greenness at the 6-digit ISCO level, she would have to aggregate it at the 3-digit level in order to obtain a reliable measure of green employment by using uniform weights (Vona (2021).

Within the SkiLMeeT project, we link 6-digit SOC greenness with 5-digit occupation data for Italy available to us at the Local Labour Market area, hence avoiding the aggregation problem, to estimate the job-to-job transition costs of green and brown occupations.

Considering these difficulties, an alternative approach consists in performing an occupation-based analysis, and then interpret the result looking at the task and skill content of occupations that emerge as “winners” and “losers”. Such an approach is used by Marin and Vona (2019) to study the heterogeneous response to a large and persistent increase in energy prices, a proxy of carbon taxation, on the demand of workers with different skills in EU countries and sectors. In the same spirit, Bachmann et al. (2024b) decompose the greening of the German labour market. They show that the greening of occupations over time ("within-effect", i.e. greening of given occupations holding occupational employment shares constant) is at least as important for the overall greening of employment as the shift in occupational employment shares ("between-effect", i.e. initially green occupations growing faster than other occupations).

As anticipated, a valid alternative is to use measures of technology exposure either with a process definition (pollution or carbon content of jobs) or with an output definition (explicit measure of technology exposure). We plan to implement the process approach for France in the SkiLMeeT project developing the work of Marin and Vona (in-progress) and the work of Graham and Knittel (2024). This approach allows to identify the occupations that are more vulnerable as exposed to cost-shocks such as the EU-ETS and carbon pricing. The output approach allows instead to identify the occupations that are more likely to benefit from green subsidies. An example to implement this approach for Europe is to use the sector-level (4-digit) measure of green production for Europe developed by Bontadini and Vona (2023)[4] and link it to granular occupation- or job-level data. A third possibility consists in using

[4] Bontadini and Vona (2023) build a list of green products merging and cleaning the lists used for the international negotiations on green product tariffs at the World Trade Organization (WTO). The authors estimate an average

ESCO, the EU equivalent of O*NET. This solution is interesting and feasible, but it faces the data constraint of the lack of aggregation of EU LFS data mentioned above.

Lastly, the most likely and promising venue in terms of data is that of OJV data, given their immense granularity and available for the EU. Saussay et al (2022) provide evidence on the characteristics of low-carbon jobs in the US using comprehensive OJV data between 2010-2019. The authors exploit valid tokenized low-carbon keywords from pre-existing and widely utilised classifications, to then apply natural language processing (NLP) using the term frequency–inverse document frequency (TF-IDF) algorithm. Low-carbon jobs have higher skill requirements across a broad range of skills, especially technical ones. However, the wage premium for low-carbon jobs has declined over time and the geographic overlap between low- and high-carbon jobs is limited. The methodology is transparent and flexible, and, given access to OJV data, can be easily replicated in different country contexts. For this project, we plan to combine this methodology with data on green production to conduct the first cross-European study on the impact of the green transition on labour markets.

3.3. Additional megatrends

3.3.1. Disruption of global value chains

The literature on the role of global value chains (GVCs) for skill demand in developed countries reveals a consistent pattern of increasing demand for high-skilled labour, driven by factors such as offshoring, technological progress and upgrading, and relative specialisation of developed countries in non-routine tasks that usually require more advanced skills. In their theoretical exploration, Grossman and Rossi-Hansberg (2008) propose that offshoring of tasks rather than goods intensifies the relative demand for skilled labour, leading to wage polarisation in developed countries.

This theoretical prediction is borne out by a number of empirical studies. Examining the combined effects of immigration and offshoring on U.S. labour markets, Ottaviano et al. (2013) find that both

share of green production of 2-2.5% in the manufacturing sector in Europe over the period 2000-2015. Assuming proportionality, as done in works using green production data, the share of green employment is then in the usual range and is significantly higher only in countries that have a comparative advantage in certain green technologies such as Germany (3-3.5%) and Denmark (up to 10%).

phenomena create opportunities in high-skill occupations while reducing job prospects for low-skilled workers. Timmer et al. (2013) focus on the European context, demonstrating that participation in GVCs boosts demand for skilled labour and contributes to wage disparities, especially for countries specialising in high-value-added segments. Autor et al. (2013) highlight the impact of Chinese import competition on the U.S. labour market, demonstrating significant job losses in manufacturing sectors predominantly affecting less-skilled workers. Hummels et al., 2014) show that offshoring increases the wages of high-skilled workers in Denmark, while low-skilled workers face wage stagnation or declines, emphasising a shift in demand towards higher skills due to global production strategies. Similarly, Feenstra and Hanson (1999) find that outsourcing and high-tech capital investments contribute to increased demand for skilled labour and higher wage inequality in the U.S., further underlining the impact of GVCs on labour market polarisation.

The studies on the impact of COVID-19 on global value chains (GVCs) highlight a significant shift in skill demand towards higher-skilled occupations, particularly in the digital and technical domains, as maintaining supply chain continuity during the pandemic increased the demand for skills in supply chain management, logistics, and digital technologies. Javorcik (2020) notes the acceleration of regionalisation and digitalisation in supply chains, leading to a higher demand for high-skilled workers adept at managing new technologies. The pandemic's impact on GVCs also materialized in a sectoral shift towards technology and healthcare, increasing the demand for high-skilled workers (Bonadio et al., 2021). Espitia et al. (2021) underscore the need for resilience in supply chains, highlighting a growing need for skills in risk management, digital technologies, and supply chain analytics. Del Rio-Chanona et al. (2020) also emphasise the shift towards higher-skilled occupations as industries integrate more automation and digital transformation to cope with supply and demand shocks.

3.3.2. Demographic change

Population ageing can have a significant impact on labour and skills shortages due to a number of factors. The demographic shift towards an older population alters the age distribution within the workforce, influencing both productivity and potential labour and skills shortages across various sectors (Maestas et al., 2023; Bloom et al., 2010; Börsch-Supan & Weiss, 2016). As a greater proportion of the population reaches retirement age, the number of individuals exiting the labour force increases, thereby reducing the overall pool of available workers. This shift is particularly pronounced in industries where older workers have been predominant, leading to more severe labour shortages in those industries (European Commission, 2023b). Furthermore, older workers frequently possess highly specialised skills and extensive experience that are challenging to replace rapidly. The departure of older workers from the workforce results in significant skills gaps, particularly in niche occupations or sectors that require years of training and experience (Hecker et al., 2021). For instance, sectors such as healthcare, engineering, and skilled trades frequently depend on the expertise of experienced professionals. The loss of these workers can have a disruptive effect on operations and a negative impact on productivity, as it takes time to train new employees to the same level of proficiency.

Conversely, some research supports the hypothesis that older individuals may engage in activity substitution between employment and voluntary work. This indicates that while ageing may contribute to labour shortages in traditional employment sectors, it may simultaneously alleviate shortages in voluntary work sectors (Eibich et al., 2022). It is possible that older workers may transition from paid employment to volunteer roles, thereby contributing valuable skills and experience to non-profit organisations and community services. This shift can serve to mitigate the labour shortages that are prevalent in the formal economy.

3.3.3. The Covid-19 pandemic

The COVID-19 pandemic induced noticeable adjustments among both employees and employers. Most importantly, it accelerated the digital transformation across various sectors, emphasizing the need for digital skills. This required both a rapid upskilling of a large group of workers and structural changes in the priorities of education systems (Tomaževič et al., 2021). However, Soh et al. (2024) provided causal evidence that in the U.S., COVID-19 has not increased the demand for digital jobs, such as I.T. specialists. In the longer term, the pandemic does not seem to have aggravated the mismatch between labour supply and demand in the US (Forsythe et al., 2022; Pizzinelli and Shibata, 2023; Soh et al., 2024).

The COVID-19 crisis seems to have altered the valuation of interpersonal tasks in the labour market. Gu and Zhong (2023) argue that the shift towards work-from-home changed the types of social skills expected from employees, with interpersonal skills being less in demand. On the supply side, Forsythe et al. (2022) show that low-skilled customer-facing jobs became less desirable in the U.S., leading to labour shortages.

Overall, the mismatch between labour supply and demand was lower during the COVID-19 crisis than during the 2008 global financial crisis, and its impact was short-lived (Pizzinelli and Shibata, 2023). Rather than creating demand for new jobs, the COVID-19 crisis altered the skills needed across many occupations. Most of the evidence refers to the U.S. labour market, which is usually more flexible than

European labour markets.. Therefore, more research is needed to verify the consequences of the COVID-19 crisis in the European context.

3.3.4. Migration

Migrants are seen as a solution to solve labour shortages (Anderson & Ruhs, 2011; Lange & Winkelmayer, 2024; Martin et al., 2023). For example, Martin et al. (2023) emphasise that the presence of migrants (EU and non-EU) is crucial to address labour shortages, particularly in the German and French labour markets, and that the skills required are fairly stable over the 2019-2021 period, except for digital skills and soft skills, which are in increased demand for some occupations. One sector that has been the subject of a growing number of studies is the health sector, where labour shortages have worsened since the COVID-19 pandemic. For example, Lange and Winkelmayer (2024) highlight that migrants from Central and Eastern Europe are reducing labour shortages in this sector, both for skilled and unskilled jobs. Regarding the role of the cross-border workers in the SkiLMeeT case study, specifically Luxembourg, Fromentin (2021) highlights that the main sectors of cross-border employment largely coincide with the sectors experiencing the most labour shortages, suggesting that cross-border employment is not sufficient to overcome shortages.

There is some evidence of a skill mismatch between migrants and natives (Jestl et al., 2015; Visintin et al., 2015). They find that overeducation is more common among migrant workers than natives, especially in low-skilled occupations. Visintin et al. (2015) also find that skill mismatch is more prevalent among migrants, although the extent of this phenomenon varies between countries of origin and destination. In this context, Ciprikis et al. (2024) and Eurofound (2023) list public policies that can help recognise foreign qualifications and better integrate migrants. Despite these studies, there seems to be a lack of analyses on how migration and cross-border commuting can help overcome skills shortages remains scarce or even absent.

SkiLMeeT considers the mentioned megatrends disruption of global value chains, demographic change and Covid whenever these factors could influence the analyses. Furthermore, SkiLMeeT provides explicit analyses of the role of migration particularly as a pathway to reduce skills gaps and mismatch which is discussed next.

4. Pathways to reduce skills gaps and mismatch

4.1. Education

4.1.1. Educational choice

Adjustments in educational choices at the secondary and post-secondary levels can be seen as a solution to skill shortages in the long run. Educational choices about the level of education and fields of study vary widely across space and time (UNESCO, 2024). The expected returns from different occupations and perceived ability are important determinants of the field of study choices. Still, differences in tastes are the dominant factor in choosing the field of study (Wiswall & Zafar, 2015). Empirical literature analysing the field of study decisions also points to students' preferences for workplace attributes (Wiswall & Zafar, 2018), students' self-confidence, and beliefs about their relative ability (Bobba et al., 2023; Goulas et al., 2022) as potential determinants.

Recent literature shows that the quality of institutions matters for the field of study choices (Alexeev et al., 2024). Using regional variation in Russia, they show that market-supporting institutions attract talents to productive activities, which is reflected in university students' choices of fields of study.

Educational decisions also respond to the economic situation, specifically changes in labour demand (Black et al., 2005; Bourassa-Viau et al., 2022). The increase in education enrolment due to a negative trade shock is gradual and visible after 3 or 4 years (Bourassa-Viau et al., 2022). However, the literature on how educational choices respond to technological progress is scarce. Related research shows that often, young workers are in jobs projected to be at high risk of automation. Still, they gradually move into jobs projected to be less exposed to automation (Cebulla, 2024).

4.1.2. Dual education

Apprenticeship training, particularly the dual system, plays a major role for occupational education in countries such as Switzerland, Germany, and Austria, and has recently been developing in Central and Eastern Europe. Rupietta and Backes-Gellner (2019) argue that the dual system facilitates knowledge diffusion within firms. This system integrates apprentices into the production process, allowing them to perform productive tasks and gain hands-on experience with new technologies. Firms that participate in apprenticeship training exhibit higher innovation outcomes compared to non-participating firms. This is attributed to the continuous flow of updated knowledge and skills from the training programs into the firms.

The Swiss VET (Vocational Education and Training) system studied by Rupietta and Backes-Gellner (2019) includes a built-in curriculum-updating process that ensures the training content remains relevant to current technological advancements. This process enhances firms' absorptive capacity and technological awareness, contributing to their innovation capabilities. The authors empirically support their hypotheses, showing that firms engaged in apprenticeship training have better innovation performance, i.e. they are more likely to adopt new technologies and implement innovative processes. The study highlights the importance of external inter-firm training courses, which are often part of the apprenticeship programs. These courses provide apprentices with exposure to new technologies that may not be available in their own firms, further enhancing knowledge diffusion and innovation. The diffusion effect of new technologies is particularly strong for mainstream firms (non-innovative SMEs), which constitute the majority of firms. These firms benefit significantly from the updated skills and knowledge brought in by apprentices. The findings suggest that policies promoting apprenticeship training and regular updates to vocational education curricula can enhance firms' innovation capabilities. This has implications for education and labour market policies aimed at fostering economic growth through innovation.

Kiener et al. (2022) study how the integration of IT skills into the curricula of the dual system affects graduates' labour market success. The study examines how IT skills are embedded within broader vocational training curricula. It highlights the importance of including IT skills as part of comprehensive skill packages to ensure that graduates are well-prepared for the demands of the modern labour market. The study finds a positive correlation between the inclusion of IT skills in vocational training and improved labour market outcomes for graduates. Specifically, graduates with IT skills are more likely to secure employment and earn higher wages compared to those without such skills.

The results from Kiener et al. (2022) show that IT skills are most effective when combined with other complementary skills. This combination enhances employability and adaptability in a rapidly changing job market. The findings also suggest that policymakers and educational institutions should prioritize the integration of IT skills into vocational training programs. Doing so could help bridge the skills gap and better prepare the workforce for future technological advancements. The authors recommend that vocational training curricula should be regularly updated to include emerging IT skills to ensure that the training remains relevant and aligned with industry needs.

In a related study, Kiener et al. (2023) study non-cognitive skills, focusing on self-competence, defined as the ability to act responsibly on one's own, considered as a crucial noncognitive skill taught in vocational training programs. The authors use machine-learning methods to identify the levels of self-competence taught from the texts of occupational training curricula. To examine the wage returns associated with three different levels of self-competence (low, medium, high), they use individual labour-market data. The study finds that the wage returns to self-competence are nonlinear as a medium level of self-competence yields higher wage returns than low or high levels. In occupations with high cognitive requirements, a high level of self-competence also generates positive wage returns.

The paper highlights the importance of the right balance between cognitive and noncognitive skills. High levels of self-competence are particularly beneficial in occupations that require high cognitive skills, indicating complementarities between these skill types. The findings suggest that vocational training programs should carefully consider the level of noncognitive skills, such as self-competence, included in their curricula. Overemphasis or underemphasis on these skills can lead to suboptimal wage outcomes. Policymakers and educators should aim to strike a balance in teaching noncognitive skills to maximize economic returns for graduates.

Cnossen et al. (2023) study the returns to skills contained in vocational training curricula more broadly. The study analyzes the content of vocational education curricula to determine the emphasis on different types of skills, specifically social, technical, and basic cognitive skills. The authors use text analysis methods to extract and categorize the skills described in the curricula of the Dutch vocational education system. The paper estimates the wage returns to these skills by linking the curriculum data to labour market outcomes of graduates.

Their findings indicate that the returns to different skills vary significantly. Technical skills generally yield higher wage returns compared to social and basic cognitive skills. The study finds that the demand for specific skills and their associated wage returns differ across sectors. For example, technical skills are more highly valued in STEM (Science, Technology, Engineering, and Mathematics) and healthcare fields, while social skills are less rewarded in high-skill service sectors. Graduates from programs with a higher focus on social skills tend to have lower wage returns compared to those from programs emphasizing technical skills. This suggests that the relative emphasis on different types of skills in vocational curricula can significantly impact the economic outcomes for graduates. The findings highlight the importance of aligning vocational education curricula with labour-market demands. Policymakers and educators should consider the varying returns to different skills when designing and updating vocational training programs. Emphasizing technical skills in vocational education could enhance the employability and earnings potential of graduates.

4.1.3. Up- and reskilling

The attention to reskilling and upskilling stems from the notion that the required skills for many occupations are changing rapidly due to the above trends. Upskilling usually refers to expanding people's existing skills set; reskilling refers to learning new skills outside of the person's existing skillset (see European Skills Agenda). Despite predictions of massive job losses due to automation (Frey & Osborne 2013/2017), employment levels in Europe have never been higher in the last century. According to the European Labour Authority (ELA 2020), a total of 28 occupations, accounting for 14% of the EU workforce in 2020 (27 million people), have been identified as facing shortages - and 19 occupations have been identified as facing major shortages. These include occupations such as welders in manufacturing, nurses in healthcare and programmers in ICT. In the context of the European Year of Skills (May 2023 – May 2024), EU Member States and social partners committed to tackle labour and skills shortages by promoting up- and reskilling. The aim is to create quality jobs and a workforce with the right skills that are essential for the EU's competitiveness. In concrete terms, this commitment would mean attracting more people into the labour market, improving working conditions, facilitating the recognition of qualifications and integrating workers from abroad.

With regard to the digital transformation (Meil & Kirov 2017), there are estimations that by 2025, 50% of all employees will need reskilling due to adopting new technology (Schwab and Zahidi, 2020). More recently, there are strong expectations that AI will transform professional skills and workplaces, increasing not only the importance of specific hard skills, but also of transversal skills (Sofia et al. 2023). However, reskilling and upskilling do not happen automatically (Kornelakis et al. 2022), but take different configurations in different societal, institutional and educational contexts (Li 2022). Central to this is the development of a learning environment (or culture) that gives people the opportunity to learn skills on the job, supplemented with flexible short-term forms of (modular) training (Kyndt et al, 2016; Cerasoli et al, 20214; Garvin et al, 2008). The European Commission therefore points out the importance of micro-credentials with which people can demonstrate which skills they have learned during their career.[5] To gain a better understanding of the conditions for reskilling and upskilling, there is a need to investigate the specific types of mechanisms for transitions - e.g. company based (transitions within large companies), sectoral based (based on existent sectoral funds, skills councils or other joint initiatives), transborder based (transitions on the basis of skills shopping in neighbouring regions or countries), market based (through the initiative of individuals); corresponding largely to the two varieties of capitalism, the liberal market economies (LME) and the coordinated market economies (CME) (Hall & Soskice 2001). This requires reexamining critically the vast stream of literature on European institutional models (e.g. Gallie et al. 2007) to understand and identify strategies that can support organisations and guide individuals toward the upskilling and reskilling challenges

4.1.4. Worker mobility, skill transferability, working conditions and well-being

SkiLMeeT aims at gaining a comprehensive understanding of the phenomenon of worker mobility, the potential skills transferability associated with job changes, and the mobility-related changes in working conditions and well-being. This is important as there is a lack of dialogue between these different strands of literature, which creates a gap in the existing body of knowledge. First, regarding worker mobility, there is evidence that digitalisation is reducing employment in some sectors while creating opportunities in others (Bachmann et al., 2025; Dauth et al., 2021). Indeed, Daut et al. (2021) show that employment loss in manufacturing sector in Germany due to robot adoption was fully offset by additional jobs in the service sector (Dauth et al., 2021). Bachmann et al. (2024a) reveal that in Europe, robots reduce job separation rates and increase job findings, particularly in Eastern and Southern EU countries characterised with low or moderate labour costs (Eastern and Southern EU countries).

Bisello et al. (2022) and Bachmann et al. (2020) show that occupational mobility patterns differ across European countries. Moreover, the greening of the economy creates new jobs opportunities (Sulich & Sołoducho-Pelc, 2022). Nevertheless, some worker groups are less vulnerable to structural change and job loss than others. For instance, robots do not increase the displacement of incumbent manufacturing workers (Dauth et al., 2021) while geographically mobile workers appear to be fully shielded from the decline in local employment opportunities after mass layoffs (Gathmann et al., 2020).

[5] https://education.ec.europa.eu/education-levels/higher-education/micro-credentials

Second, regarding skills transferability, some studies examine the overlap of skills from one occupation to another. Alabdulkareem et al. (2018) highlight that in the United States, there is a notable polarization of skills into two distinct clusters. These clusters feature the specific social-cognitive and sensory-physical skills required for high- and low-wage occupations, respectively. The study highlights that this polarised skill clustering will restrict the career mobility of individual workers, with those with low skills being "stuck" in roles requiring low-wage skills.

Finally, the working conditions including the changes in wages and well-being of workers before and after job-to-job transitions are also essential to study and a key question is: why do workers decide to change jobs? On the one hand, they can look for a better match and improve their wage. One strand of the literature attempts to disentangle the wage motive from a better match between a particular worker's skills and the needs of a particular firm. Jinkins & Morin (2018) highlight that changes in the quality of the worker-firm match explain most of the variance in wage growth experienced by job-to-job movers. Diaz-Serrano & Teruel-Carrizosa (2022) show that job-to-job transition increases individuals' hourly earnings. Nevertheless, this particular strand of the literature does not provide any information on the skills transferability. Bachmann et al. (2020) estimate an occupational mobility is strongly associated with earnings mobility. Those who change occupation are more likely to experience a downward rather than an upward earnings transition, whereas those who changing occupation voluntarily are more often followed by an upward wage transition.

On the other hand, workers may seek to improve their non-monetary working conditions and their well-being. Some papers in this strand of the literature introduce the concept of skills but mainly in a basic manner. Indeed, many studies investigate the relationship between a worker's years of education and job mismatch, and its impact on employee outcomes. For example, Bender & Heywood (2009) underline that education mismatch is associated with worse outcomes: lower wages, lower job satisfaction, and higher turnover. Some studies treat these mismatched workers as a homogeneous group (e.g., Kinsler & Pavan, 2015), while others recognize that individuals can be mismatched for a variety of reasons. Researchers have identified both demand-side and supply-side reasons for educational mismatch. Demand-side reasons include the unavailability of jobs in the worker's field of study or the lack of suitable job openings that match their educational qualifications (Bender & Heywood, 2009; Robst, 2007). Supply-side reasons refer to factors such as job satisfaction and personal preferences. For example, workers may choose to work in a job that does not require their level of education due to personal fulfilment. For instance, Martin (2020) finds that employees who are motivated by intrinsic and personal growth factors are less likely to leave their current position, while those who are motivated by external rewards or external pressures are more likely to do so.

Skill mismatch in relation to job satisfaction has been studied using a broad measurement, i.e. employees' perceptions of skill mismatch in their jobs, with the evidence currently being inconclusive. While Sánchez-Sánchez & McGuinness (2015) highlight that being over-skilled reduces job satisfaction, and being under-skilled increases job satisfaction, Badillo Amador et al., (2012), find the opposite. Diaz-Serrano & Teruel-Carrizosa (2022) provide evidence showing that job-to-job transition permit to improve job satisfaction.

In order to improve the assessment, and therefore enable a better design of appropriate policy strategies to reduce skills gaps and shortages, it is important to note that few studies have look at the role played by working conditions in labour or skills shortages. In the case of low-skilled occupations, Hauret & Martin (2023) observe that pay conditions in occupations in shortage are slightly more favourable than in closed occupations since they are less reliant on bonuses, overtime and shift work. Coutrot (2022) highlights that firms encountering recruitment difficulties frequently cite wage and working condition issues as causes. The perceived inability to do a good job, the unpredictability of working hours and the need to work at a fast pace contribute to recruitment difficulties.

SkiLMeeT provides extensive analyses of pathways to reduce skills shortages and mismatches. These analyses are related to worker mobility, including job-to-job mobility, occupational mobility, and migration, the role of skills transferability in the context of (potential) worker mobility, educational choice of young people, and training and further education.

5. Conclusion

This document has provided an overview of the scientific literature on skills gaps, skill and labour shortages, and mismatch, and has indicated the respective contributions of the SkiLMeeT project. Given that the existing literature is vast, and that there exist a number of recent overviews of the literature, the aim was to explore the scientific literature most relevant for SkiLMeeT. The overview therefore focused on some considerations regarding the relevant concepts and measurement; the drivers of skills gaps and shortages and mismatch considered in SkiLMeeT, i.e. mainly the technological and green transitions, but also other megatrends; and pathways to reduce skills gaps and shortages and mismatch considered in SkilMeeT, i.e. education (educational choice, the dual education system, re- and upskilling) and worker mobility.

For the SkilMeeT project, this document is a starting point for the entire analysis. It is especially important for one of the next steps of the project, i.e. the elaboration of the conceptual framework (Deliverable 1.2) which will also consider additional initiatives that provide indicators on skills gaps and shortages, amongst others the SkiLMeeT sister projects SkillsPulse, SKILLAB and TRAILS.

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